Amendment to the Specification:

Please replace existing paragraph [0001] with the following replacement paragraph as follows:

[0001] This application claims the benefit of priority to provisional application serial number 60/446,596 ("the '596 application"), filed February 11th, 2003. The '596 application is hereby incorporated by reference in its entirety. <u>A copy of the '596 application is attached hereto as an appendix.</u>

Please replace existing paragraph [0015] with the following replacement paragraph as follows:

[0015] FIG. 1 depicts a flow chart of the basic technique implemented by the present invention. The calculations performed by the various portions of FIG. 1 are included in the provisional application that is incorporated herein by reference, and such mathematical equations will not be repeated again herein. <u>For reference, the reader is directed to the copy of the '596 application which is attached hereto as an appendix.</u>

Please replace existing paragraph [0017] with the following replacement paragraph as follows:

[0017] This training data is utilized at block 103 in order to compute the discriminating feature analysis (DFA) vector of the training images. The DFA vector is a novel featured vector with enhanced discriminating power for face detection. The DFA representation, shown for example in FIG. 2 hereof, combines the input image, its 1-D Haar wavelet representation, and its amplitude projections. The DFA representation of the training images may be calculated from Equation 6 in the provisional application incorporated herein by reference. The derivation of such equation is shown at pages 5-6 of said provisional. The output of Equation 6 represents the combination of the image, its 1-D Haar wavelet representation, and its amplitude projections. <u>The subject matter of pages 5-6 of the incorporated and attached provisional is reproduced in the following:</u>

3.1 Discriminating Feature Analysis

[0017.1] The discriminating feature analysis derives a new feature vector with enhanced discriminating power for face detection, by combining the input image, its 1-D Haar wavelet representation, and its amplitude projections. While the Haar wavelet representation has been shown effective for human face and pedestrian detection [14], the amplitude projections are able

to capture the vertical symmetric distributions and the horizontal characteristics of human face images.

[0017.2] Let $I(i, j) \in \mathbb{R}^{m \times n}$ represent an input image (e.g. training images for face and nonface classes, or subimages of test images), and $\mathbf{X} \in \mathbb{R}^{mn}$ be the vector formed by concatenating the rows (or columns) of $I(i, j)$. The 1-D Haar representation of $I(i, j)$ yields two images, $I_h(i, j) \in \mathbb{R}^{(m-1) \times n}$ and $I_v(i,j) \in \mathbb{R}^{m \times (n-1)}$, corresponding to the horizontal and vertical difference images, respectively.

$$I_h(i, j) = I(i + 1, j) - I(i, j) \qquad 1 \leq i < m,\ 1 \leq j < n \tag{1}$$

$$I_v(i, j) = I(i, j + 1) - I(i, j) \qquad 1 \leq I \leq m,\ 1 \leq j < n \tag{2}$$

[0017.3] Let $\mathbf{X}_h \in \mathbb{R}^{(m-1)n}$ and $\mathbf{X}_v \in \mathbb{R}^{m(n-1)}$ be the vectors formed by concatenating the rows (or columns) of $I_h(i, j)$ and $I_v(i, j)$ respectively.

[0017.4] The amplitude projections of $I(i, j)$ along its rows and columns form the horizontal (row) and vertical (column) projections, $\mathbf{X}_r \in \mathbb{R}^m$ and $\mathbf{X}_c \in \mathbb{R}^n$, respectively.

$$\mathrm{X}_r(i) = \sum_{j=1}^{n} I(i, j) \qquad 1 \leq i \leq m \tag{3}$$

$$\mathrm{X}_c(j) = \sum_{i=1}^{m} I(i, j) \qquad 1 \leq j \leq n \tag{4}$$

[0017.5] Before forming a new feature vector, the vectors X, X_h, X_v, X_r and X_c are normalized by subtracting the means of their components and dividing by their standard deviations, respectively. Let $\hat{\mathrm{X}}$, $\hat{\mathrm{X}}_h$, $\hat{\mathrm{X}}_v$, $\hat{\mathrm{X}}_r$, and $\hat{\mathrm{X}}_c$, be the normalized vectors. A new feature vector $\tilde{\mathrm{Y}} \in \mathbb{R}^N$ is defined as the concatenation of the normalized vectors:

$$\tilde{\mathrm{Y}} = (\hat{\mathrm{X}}^t \hat{\mathrm{X}}_h^t \hat{\mathrm{X}}_v^t \hat{\mathrm{X}}_r^t \hat{\mathrm{X}}_c^t)^t \tag{5}$$

[0017.6] where t is the transpose operator, and $N = 3mn$ is the dimensionality of the feature vector $\tilde{\mathrm{Y}}$. Finally, the normalized vector of $\tilde{\mathrm{Y}}$ defines the discriminating feature vector, $\mathrm{Y} \in \mathbb{R}^N$,

which is the feature vector for the multiple frontal face detection system, and which combines the input image, its 1-D Haar wavelet representation, and its amplitude projections for enhanced discriminating power:

$$\mathrm{Y} = \frac{\tilde{\mathrm{Y}} - \mu}{\sigma} \qquad (6)$$

[0017.7] where μ and σ are the mean and the standard deviation of the components of $\tilde{\mathrm{Y}}$, respectively.

Please replace existing paragraph [0019] with the following replacement paragraph as follows:

[0019] The modeling of the face and non-face classes is represented generally by operational block 105 in FIG. 1. The conditional probability density function of the face class can be estimated using a single multivariate Gaussian distribution, rather than up to six Gaussian clusters as utilized by most prior art systems. The monitoring of the face class is accomplished in accordance with Equation 13 in the incorporated provisional application. ~~That equation~~ The equation which follows can be used to model the face class.

$$\ln[p(\mathrm{Y} \mid \omega_f)] = -\frac{1}{2}\left\{ \sum_{i=1}^{M} \frac{z_i^2}{\lambda_i} + \frac{\|\mathrm{Y} - \mathrm{M}_f\|^2 - \sum_{i=1}^{M} z_i^2}{\rho} + \ln\left(\prod_{i=1}^{M} \lambda_i\right) + (N - M)\ln\rho + N\ln(2\pi) \right\} \qquad (13)$$

Please replace existing paragraph [0020] with the following replacement paragraph as follows:

[0020] Continuing with operational block 105, the nonface class modeling starts with the generation of nonface samples by applying Equation 13 to natural images that do not contain any human faces at all. Those subimages of the natural images that lie closest to the face class are chosen as training samples for the estimation of the conditional probability density function of the nonface class, which is also modeled as a single multivariate Gaussian distribution. The conditional density function of the nonface class is estimated as Equation 18 in the incorporated provisional application. Accordingly, at the completion of block 105, Equations 13 and 18 have

already been utilized to calculate the conditional PDFs for both face and nonface classes from a single multivariate Gaussian distribution. Equation 18 follows.

$$\ln[p(Y \mid \omega_n)] = -\frac{1}{2}\left\{\sum_{i=1}^{M}\frac{u_i^{\,2}}{\lambda_i^{(n)}} + \frac{\|Y - M_n\|^2 - \sum_{i=1}^{M} u_i^{\,2}}{\varepsilon} + \ln\left(\prod_{i=1}^{M}\lambda_i^{(n)}\right) + (N-M)\ln\varepsilon + N\ln(2\pi)\right\} \tag{18}$$

Please replace existing paragraph [0023] with the following replacement paragraph as follows:

[0023] To perform such classification, control is transferred to block 108 where the BDF method applies the Bayesian classifier for multiple frontal face detection. The Bayesian classifier provided at Equations 19-25 of the incorporated provisional application is executed upon the DFA of the input image. The Bayesian classifier will then determine, according to Equation 25 of the incorporated provisional, whether the image or subimage being examined is a face or a nonface class. The equations 19-25 define what is termed herein a Bayesian classifier. Equations 19-25 and an explanation thereof follow.

3.3 The Bayesian Classifier for Multiple Frontal Face Detection

[0023.1]After modeling the conditional PDFs of the face and nonface classes, the BDF method applies the Bayes classifier for multiple frontal face detection, since the Bayes classifier yields the minimum error when the underlying PDFs are known. This error, called the Bayes error, is the optimal measure for feature effectiveness when classification is of concern, since it is a measure of class separability [3].

[0023.2]Let $Y \in \mathbb{R}^N$ be the discriminating feature vector constructed from an input pattern, i.e., a subimage of some test image (see Sect. 3.1). Let the a *posteriori* probabilities of face class (ω_f) and nonface class (ω_n) given Y be $P(\omega_f \mid Y)$ and $P(\omega_n \mid Y)$, respectively. The pattern is classified to the face class or the nonface class according to the Bayes decision rule for minimum error [3]:

$$Y \in \begin{cases} \omega_f & if \quad P(\omega_f \mid Y > P(\omega_n \mid Y \\ \omega_n & otherwise \end{cases} \tag{19}$$

[0023.3]Note that the Bayes decision rule optimizes the class separability in the sense of the Bayes error, hence should yield the best performance on face detection.

[0023.4]The a *posteriori* probabilities, $P(\omega_f \mid \mathrm{Y})$ and $P(\omega_n \mid \mathrm{Y})$, can be computed from the conditional PDFs as defined in Sects. 3.2.1 and 3.2.2 using the Bayes theorem.

$$P(\omega_f \mid \mathrm{Y}) = \frac{P(\omega_f)p(\mathrm{Y} \mid \omega_f)}{p(\mathrm{Y})}, \qquad P(\omega_n \mid \mathrm{Y}) = \frac{P(\omega_n)p(\mathrm{Y} \mid \omega_n)}{p(\mathrm{Y})} \tag{20}$$

[0023.5]where $P(\omega_f)$ and $P(\omega_n)$ are the a *priori* probabilities of face class ω_f and nonface class ω_n, respectively, and $p(\mathrm{Y})$ is the mixture density function.

[0023.6]From Eqs. 13, 18, and 20, the Bayes decision rule for face detection is then defined as follows:

$$\mathrm{Y} \in \begin{cases} \omega_f & \text{if} \quad \delta_f + \tau < \delta_n \\ \omega_n & \text{otherwise} \end{cases} \tag{21}$$

[0023.07]where δ_f, δ_n, and τ are as follows:

$$\delta_f = \sum_{i=1}^{M} \frac{z_1^2}{\lambda_i} + \frac{\|\mathrm{Y} - \mathrm{M}_f\|^2 - \sum_{i=1}^{M} z_i^2}{} + \ln\left(\prod_{i=1}^{M} \lambda_i\right) + (N-M)\ln\rho \tag{22}$$

$$\delta_n = \sum_{i=1}^{M} \frac{u_1^2}{\lambda_i^{(n)}} + \frac{\|\mathrm{Y} - \mathrm{M}_n\|^2 - \sum_{i=1}^{M} u_i^2}{} + \ln\left(\prod_{i=1}^{M} \lambda_i^{(n)}\right) + (N-M)\ln\varepsilon \tag{23}$$

$$\tau = 2\ln\left[\frac{P(\omega_n)}{P(\omega_f)}\right] \tag{24}$$

[0023.8] δ_f and δ_n can be calculated from the input pattern Y, the face class parameters (the mean face, the first M eigenvectors, and the eigenvalues), and the nonface class parameters (the

mean nonface, the first M eigenvectors, and the eigenvalues). τ is constant which functions as a control parameter — the larger the value is the fewer the false detections are. To further control the false detection rate, the BDF method introduces another control parameter, θ, to the face detection system, such that

$$Y \in \begin{cases} \omega_f & if \quad (\delta_f < \theta) and (\delta_f + \tau < \delta_n) \\ \omega_n & otherwise \end{cases} \tag{25}$$

[0023.9]The control parameters, τ and θ, are empirically chosen for the face detection system.